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Intergenerational Poverty in Europe: A Latent Class Analysis

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Abstract

This paper investigates the intergenerational transmission of poverty and how it varies across thirty European countries using retrospective reports on childhood household circumstances from the 2019 EU-SILC ad hoc intergenerational module. Latent class analysis is employed as it allows all the available information to be incorporated to estimate current and childhood poverty with a minimum of structure imposed. For each generation, the two latent classes distinguished are seen to be distinct in terms of the prevalence of disadvantage. The intergenerational association between current and childhood poverty is assessed via transition matrices and summary mobility indices. This shows substantial variation in the extent and nature of intergenerational association across the countries covered, with a high degree of consistency between. Household income is not available for the parental generation but omitting it from the latent class model for current poverty made little difference to the country mobility rankings.

Keywords: Poverty, mobility, intergenerational transmission, disadvantage

JEL Codes: D31, D63, O40

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1 Introduction

The transmission of poverty and disadvantage from one generation to the next is a particularly salient aspect of broader intergenerational mobility and inequality of opportunity, and is a central concern for anti-poverty policies. The many distinct, inter-related channels through which the experience of poverty in childhood can increase the risk of adverse outcomes in adulthood are the subject of very substantial research literatures not only in economics but also in sociology, psychology and public health (Duncan et al., 1998, 2012; Van Lancker and Vinck, 2019). However, only a small minority of these studies focus directly on poverty in both parental and current generations, and most of the ones that do so deal with individual countries rather than capturing how the intergenerational persistence of poverty *per se* varies across countries.

Underlying the interest in such a comparative analysis is the search for improved understanding of the complex processes involved, to aid in the design of policies to reduce childhood poverty and weaken its link with later disadvantage. 'Breaking the vicious cycle' from one generation to the next now plays a major role in anti-poverty strategies (De Schutter et al., 2023). Identifying countries that have been more versus less successful in weakening that intergenerational poverty link is one starting-point in the complex and challenging task of teasing out which sets of institutions and policies help to do so. A recent comparative analysis by Parolin et al. (2023) brings together long-running panel data for five countries to measure poverty in income terms in a comparable fashion across generations and countries. Here by contrast we do not have information on household income in childhood, but exploit recently-available data on other aspects of childhood circumstances that allow thirty European countries to be covered. While descriptive in nature, our comparative analysis of this wide range of countries aims to provide a point of departure for subsequent investigation of the role of institutions, policies and other aspects of the country context.

These data are from a specially-designed intergenerational module incorporated into the EU Statistics on Income and Living Standards (EU-SILC) data-gathering framework in 2019. The retrospective information it obtained about the childhood circumstances of respondents does not include household income but does cover a range of other relevant information, alongside the broader set of information about the current circumstances of responding households, including their income, used to produce the measures of poverty and social exclusion employed by the European Union. Using the available information to capture poverty in both current and parental households poses a real challenge, which we address here using latent class analysis, a flexible analytical approach that allows all the available relevant information to be incorporated in a fashion consistent with the multidimensional nature of the underlying concept. This approach has been applied previously in studying poverty as well as, for example, social class (Moisio, 2004; Savage et al., 2013); a core contribution of this paper is to demonstrate how latent class analysis provides a flexible way to incorporate the complex structure of the data available, enabling a harmonised analysis of intergenerational poverty transmission/persistence across most European countries.

We identify two latent classes in each generation that are seen to be clearly distinct in terms of prevalence of disadvantage. The strength of intergenerational association between childhood and current poverty can then be assessed via transition matrices and summary mobility indices, and is seen to vary substantially across the 30 European countries covered. Omitting household income from the latent class model for current poverty, restricting that to the types of variable available for the parental generation, is seen to have little impact on the country rankings which are also seen to be reasonably robust with respect to other key modelling choices such as the number of latent classes.

The paper is organized as follows. Section 2 reviews the literature on intergenerational poverty persistence, noting the theoretical context and bringing out the data and methods generally used to study it. Section 3 describes the data we exploit, which underpin the analytical method employed which is described in Section 4. Section 5 sets out the results for the classification of households as poor or not in the parental and current generation and how this relates to the underlying variables incorporated in the model. On the basis of this classification Section 6 then compares the degree of intergenerational association between parental and current poverty across European countries by presenting transition matrices capturing the relationship between childhood and current poverty as well as summary measures of mobility/persistence derived from them. Section 7 assesses the robustness and reliability of the findings, in terms of key analytical choices and the nature of the information on which they rest. Finally, Section 8 brings together key findings and discusses their strengths and limitations as well as implications including for future research.

2 Background and Context

An extensive literature across various disciplines has established that poverty in childhood is strongly associated with poorer outcomes for children's wellbeing and healthy development (Duncan et al., 1998, 2012; Van Lancker and Vinck, 2019). It points to a complex set of causal channels involving both material living circumstances in childhood and the physical and psychological impacts these have on parents and children, underpinned for example by a resource and investment model in which lack of income/economic resources limit parents' capacity to buy goods, services and opportunities for their children (Duncan et al., 2017) or a family stress model in which poverty increases parental stress, parental depression and relationship conflict and affects parenting behaviours (Cooper and Stewart, 2013). The stresses associated with poverty may also negatively affect both parents' decision-making and children's physiological and psychological development. These channels of influence operate against the background of structures, institutions and policies in place affecting both the severity of childhood poverty and the impact it has on various later outcomes. This literature is, however, mostly focused on the impact of childhood poverty on adult outcomes other than poverty, and on national or local contexts rather than employing a comparative perspective. In parallel, the extensive comparative research literature on intergenerational mobility has for the most part been framed in terms of earnings, income, education, social class and more recently inequality of opportunity (see for example Jäntti et al., 2006; Marrero and Rodríguez, 2012; Brunori et al., 2013; Corak et al., 2014; Bratberg et al., 2017; Narayan et al., 2018; Brunori et al., 2023) and have little to say directly about the intergenerational persistence of poverty. One cannot infer conclusions about intergenerational poverty even from from studies measuring mobility from the bottom of the income distribution, as they focus on particular income groups rather than those below poverty thresholds, may not adjust income for household size/composition, and may not include all income sources (Nolan, 2023). Poverty transmission has distinctive features compared with intergenerational mobility more broadly, with specific (in degree if not always in kind) interrelated 'poverty traps', and this serves to motivate the particular interest in intergenerational poverty from both research and policy perspectives.

Some individual country studies have exploited longitudinal survey or administrative data on income to assess the intergenerational persistence of poverty measured vis-a-vis poverty thresholds derived in different ways. These have most often been for the USA, often exploiting the Panel Study on Income Dynamics (see for example Corcoran and Adams, 1997; Chetty et al., 2014; Mitnik et al., 2015) but are also available for some other rich countries including Great Britain, Australia, and Germany (see Jenkins and Siedler, 2007; Nolan, 2023 for reviews). Seeking to draw valid comparative conclusions from these individual country studies is highly problematic due to differences in the methods and poverty measures they employ.

A recent comparative study also employs income to measure poverty in both generations Parolin et al. (2023) by bringing together long-running panel data for five countries, reporting that intergenerational poverty persistence measured that way is much stronger in the USA than Denmark and Germany with Australia and the UK in between. Some other comparative studies, mostly relying on data from earlier rounds of the EU-SILC intergenerational module from 2005 and 2011, seek to relate current poverty to various related aspects of parental circumstances but without aiming to capture childhood poverty. Whelan et al. (2013) for example examined the relationship between current poverty status and parental social class and (retrospectively reported) childhood financial difficulties.

Serafino and Tonkin (2014) analysed the extent to which childhood factors such as parents' education level and employment status help to predict current income poverty and material deprivation in sixteen European countries. Bellani and Bia (2019) examined the relationship between current income poverty and retrospective reports on the extent of financial problems in the parental household.

Here we use the information available on childhood circumstances from the more recent 2019 EU-SILC module, which we describe in detail in the next section, in a novel way that seeks to capture poverty/ multidimensional disadvantage. The fact that income information is not available for the parental generation is a serious limitation but not a disabling one for this purpose. While poverty in rich countries is most often measured on the basis of household income this is widely acknowledged to have serious limitations, information other than income has much to offer in measuring poverty and exclusion, and a range of information can be employed to capture what is widely thought of as its multidimensional nature (on which see for example Alkire and Foster, 2011; Alkire et al., 2014; Decancq et al., 2019; Whelan et al., 2014; UNDP, 2023). Another recent study by Bavaro et al. (2024) exploit the same data to also assess intergenerational poverty persistence across European countries, but with a different analytic approach which involves the identification of poor parental households by applying a cut-off on an aggregate index of deprivation/disadvantage based on them. Here instead we employ latent class analysis which, as outlined in Section 4, does not involve imposing such a structure/threshold but rather 'lets the data speak'. The nature of this contrast will be clearer in light of the specifics of the indicators available, to which we turn in the next section.

3 Data

EU-SILC each year provides the cross-sectional household survey data from which Eurostat produce the official EU statistics on poverty and social inclusion, and also serves as an enormously rich foundation for research on poverty, inequality and related topics. The wealth of data it on the current circumstances of responding households includes disposable household income and an extensive set of material deprivation indicators that have been central to analysis of poverty levels and trends. To study intergenerational relationships one of course also needs information about the parental household and childhood economic circumstances of respondents. The data we exploit to study the intergenerational transmission of poverty and disdavantage come from the 2019 EU-SILC ad hoc module on intergenerational transmission of disadvantages.

Additional modules on various topics are included with EU-SILC each year, and the 2019 module is similar to the intergenerational modules included in the 2005 and 2011 EU-SILC, on which the comparative studies by Whelan et al. (2013); Serafino and Tonkin

(2014); Bellani and Bia (2019) mentioned in the previous section were based. (A further intergenerational module was included in the 2023 round of EU-SILC, from which only limited data is currently available.) These ad hoc modules contain retrospective questions across respondents aged between 25 and 59 years old on the socioeconomic status and related characteristics of their parents when respondents were around 14 years of age.[1] The retrospective questions on the parents include their country of birth, citizenship, highest educational level, activity status, managerial position, and main occupation for both the respondent's father and mother.

By dichotomising the information coming from the retrospective variables we identify four binary dimensions of parental poverty. The first is the social class; we define as part of the disadvantaged class those parents who were both either working in semi-skilled/unskilled routine occupations, unemployed or working in the home.[2] The second is the educational level; the disadvantaged class is made up of parents who both attained only lower secondary education. The third dimension we term economic hardship, based on the reported financial condition in the respondent's childhood on a six-point scale from 'very bad' to 'very good', with those in bad or very bad conditions being counted here as experiencing such hardship. The fourth dimension is material and social deprivation, based on three items (basic school needs in terms of books and equipment, a daily meal with meat, chicken, fish or vegetarian equivalent, and a week's annual holiday away from home), where we count as deprived those who were not able to afford school needs and holidays or a daily meal and holidays. (Note that one could avoid dichotomising each of these four domains, instead incorporating the full range of values for each in the latent class model; however, dichotomising can be seen as consistent with the binary nature of the underlying poverty concept and produces results that distinguish more clearly between the latent classes.)

Alongside this information for the parental generation EU-SILC has a wealth of data on the current situation of the respondents' household. For our purposes this includes household income, measured in great detail by income source and household recipient, used in producing relative income poverty measures including the 'at risk of poverty' indicator employed by the EU. It also includes occupation and the ESec social class measure derived from it, as well as educational level attained, for adult household members. It includes responses to a question which taps into perceived financial difficulties but differs from retrospective question on that topic in the ad hoc module, instead probing how much difficulty the household faces in 'making ends meet'. Finally, information is available on a wide range of material deprivation items, used alongside relative income poverty (and household worklessness) to produce the measure of poverty and social exclusion that

[1] In most countries this includes all household members in that age range but only the 'selected respondents' in what are known as 'register countries', mostly Nordics, which rely heavily on data administrative sources.

[2] We employ the European Social Class Scale ESec.

features among the EU's current objectives in the social sphere.[3]

We follow the same logic adopted for the parental generation and proceed to dichotomize the information from the current generation in order to obtain dimensions of current poverty. The first dimension is the conventional at-risk-of-poverty rate as measured by Eurostat comparing household equivalised disposable income with a relative income threshold set at 60 per cent of the median. We have this income information only for the current generation, whereas the other four dimensions are shared across the generations though measured in exactly the same way only for two. The second dimension is social class, where again we take as working class those working in semi/unskilled routine work, unemployed, or working in the home. The third is educational attainment, where those with below secondary education only are taken as disadvantaged. The fourth dimension is economic hardship, measured in terms of the reported ability to make ends meet on a six-point scale where the disadvantaged are taken to be those reporting difficulty or great difficulty. The final dimension is social and material deprivation, where we employ the 13-item index used by Eurostat and the threshold of seven or higher to distinguish the disadvantaged.

This means we have four dimensions for parental circumstances and five for current circumstances. For each there are missing values in the data, especially for parental circumstances, so we limit our analysis to households that have complete dimensional information for both generations. About 15% of the total initial sample is excluded on this basis. The total sample for analysis amounts to 187,220 observations in 30 European countries.

Table 1 shows the correlation between these dimensions for each of the generations. Overall these correlations are positive but relatively low, from 0.14 to 0.37. In some cases the correlations between dimensions are similar between generations, whereas between social class as well as hardship and education the correlations are roughly 50% larger for the current than for the parental generation. Overall, the highest correlations are between hardship and deprivation, while the weakest correlations are between deprivation and education.

These relatively low correlations suggest that the different dimensions are indeed contributing complementary information. The central challenge with which this paper engages is how best to employ this range of information to capture poverty in both the current and parental households of respondents, and on that basis measure how much coming from a

[3] Keep home adequately warm, One-week annual holiday away from home, Afford a meal with meat, chicken, fish (or vegetarian equivalent), Capacity to face unexpected financial expenses, Have a car, Arrears, Replacing worn-out furniture, Having internet connection, Replacing worn-out clothes, Having two pairs of properly fitting shoes, Spending a small amount of money each week on him/herself, Having regular leisure activities, Getting together with friends/family at least once a month.

Table 1: Cross-correlations between dimensions, parental and current generation

Parents	–	Education	Social Class	Hardship
Social Class		0.246 (0.002)		
Hardship		0.152 (0.002)	0.151 (0.002)	
Deprivation		0.171 (0.002)	0.136 (0.002)	0.369 (0.002)
Current	Income	Education	Social Class	Hardship
Education	0.224 (0.002)			
Social Class	0.281 (0.002)	0.292 (0.002)		
Hardship	0.279 (0.002)	0.224 (0.002)	0.255 (0.002)	
Deprivation	0.266 (0.002)	0.178 (0.002)	0.202 (0.002)	0.370 (0.002)

Notes: Standard errors in parentheses. **Source**: Authors' elaborations' based on EU-SILC 2019.

poor household increases the likelihood of now being in a poor household. Latent class analysis has significant advantages in this context, as the next section describes in detail.

4 Latent Class modeling

Latent variable models have been quite widely employed in studies of poverty, material deprivation, and economic and social vulnerability. Moisio (2004) for example employs a latent class model to test the validity of multidimensional poverty measurement, and Whelan and Maître (2005) conduct a latent class analysis to study vulnerability to social exclusion in a set of European countries Krishnakumar (2008) approach similar methodological questions employing other statistical models (principal component analysis, factor analysis, SEM, MIMIC). Dotto et al. (2018) focus on the measurement of social and material deprivation to incorporate information on deprivation items in a more satisfactory way than simple counts. A related stream of literature studies vulnerability to poverty from a dynamic perspective using latent transition analysis (Acconcia et al., 2020; Gallardo, 2018). Similar models have also been used to study measurement error in poverty dynamics (Breen and Moisio, 2004) as well as intergenerational mobility in terms of income (Bavaro and Tullio (2023).

Here we use latent class models to study the intergenerational transmission of multidimensional poverty, estimating separate latent class models for the current and parental generation/household. The latent class model is appropriate because i) the variables available as described in Section 3 are categorical and the model is suitable for dealing with information in this form (Skrondal and Rabe-Hesketh, 2004); ii) the number of variables differs between the generations, ruling out the use of a latent Markov model (as in for example Bavaro and Tullio, 2023) that needs common information for both; iii) given the nature of the data, latent class models allow us to use all the available information efficiently to construct multidimensional measures of poverty across generations.

A latent class model (LCM) is defined as a measurement model relating the categorical latent variable to discrete manifest variables, based on the assumption that the population is composed of unobservable subgroups (or latent classes) of individuals, sharing common characteristics related to a latent variable of interest (Lazarsfeld and Henry, 1969). LCM aims to cluster individuals in homogenous latent classes based on observed responses to categorical variables (or items). The main assumption of these models is that of local independence: it is assumed that observed associations between manifest variables depend on the relationship between latent and manifest variables so if we hold the latent variable constant, manifest variables should be statistically independent from each other.[4]

We describe the LCM starting from $Y_{i,j}$ which is the categorical response variable for subject i to item j, with $i = 1, \ldots, n$ and $j = 1, \ldots, Ji$; y is the observed value of $Y_{i,j}$; $\mathbf{Y}_i = (Y_{i,1}, \ldots, Y_{i,J})$ is the vector of items for subject i; U_i is the discrete latent variable for subject i; ξ_u is the value assumed by U_i, with $u = 1 \ldots, k$ where k is the number of latent classes. The local independence assumption implies that, given the latent class $U_i = u$, the probability of answering Y_{ij} is independent of probability of answering Y_{il}, for $j \neq l$.

The manifest distribution of the response vector $\mathbf{Y}_i$ is as follows:

$$p(\mathbf{y}) = p(\mathbf{Y}_i = \mathbf{y}) = \sum_{u=1}^{k} \pi_u p_u(\mathbf{y}), \tag{1}$$

that is composed by the mass probability (or weight) that subject i belongs to class u:

$$\pi_u = p(U_i = \xi_u) \quad ; \quad \sum_u \pi_u = 1; \pi_i > 0 \tag{2}$$

and the conditional probability of answering y, given the latent class u, that, assuming local independence, coincides with the following:

$$p_u(\mathbf{y}) = p(\mathbf{Y}_i = \mathbf{y} | U_i = \xi_u) = \prod_{j=1}^{J_i} p(Y_{ij} = y | U_i = \xi_u) \tag{3}$$

The LCM is estimated by the maximization of the log-likelihood:

$$l(\boldsymbol{\theta}) = \sum_{i=1}^{n} \log p(\mathbf{Y}_i = \mathbf{y}) = \sum_{i=1}^{n} \log \sum_{u=1}^{k} \pi_u p_u(\mathbf{y}_i) \tag{4}$$

where $\boldsymbol{\theta}$ is the vector of free model parameters. The log-likelihood $l(\boldsymbol{\theta})$ may be efficiently maximized through an Expectation-Maximization (EM) algorithm (Dempster et al., 1977).

[4]For additional details on LCMs and their applications see, inter alia, Vermunt et al. (1999); Hagenaars and McCutcheon (2002); Skrondal and Rabe-Hesketh (2004).

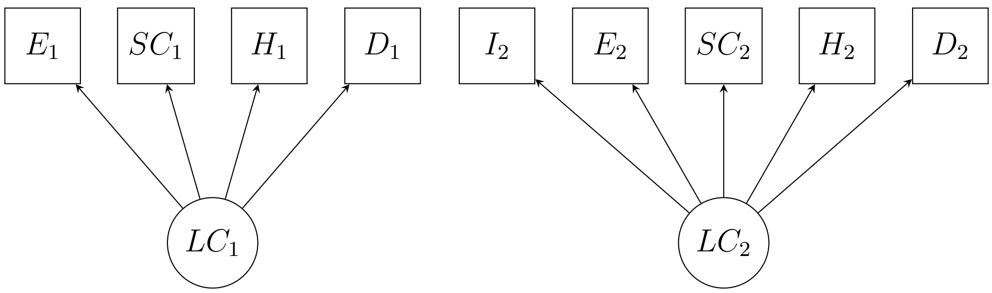
After the parameter estimation, each individual i may be allocated to one of the k latent classes on the basis of the highest estimated posterior probability.

In our the baseline model, we adopt two main assumptions: i) *maximum information*: we use the maximum amount of poverty-related variables in both the generations; ii) *latent class duality*: we assume the number of latent classes to be equal to two.

These assumptions rule out models in which we use subsets of the available variables, for instance depending on other priors or model performance,as well as models where we identify the latent poverty class in a two-step approach where we first select the best number of classes (using the standard statistical criterion, BIC or AIC) and then we select one of these classes as representing poverty. In Section 7 we relax both these assumptions, dropping income poverty from the latent class model for the current generation so the same set of dimensions is used for both generations and also discussing results allowing more than two latent classes.

The path diagram of the model is shown in Figure 1. The categorical response variables based on income (I), education (E), social class (SC), hardship (H) and deprivation (D) are denoted by squares while the latent classes (LC) are denoted by circles. Both observed and latent variables have subscripts which denote the reference generation (parental, 1, or current, 2). For the parental generation we have four categorical response variables, while for the current generation we have five.

Figure 1: *Path diagram of the model*



The model is estimated using the R-Package *PoLCA* (Linzer and Lewis, 2011).

5 Results: the Estimated Latent Classes

We now present our results, focusing first in this section on our measures of latent multidimensional poverty and the nature of their association with the underlying variables. Based on the model described in Section 4 we allocate all households to one of two possible latent classes for the current and the parental generations. (While identifying the latent multidimensional poverty class, for brevity we will mostly simply use the label 'poor'.)

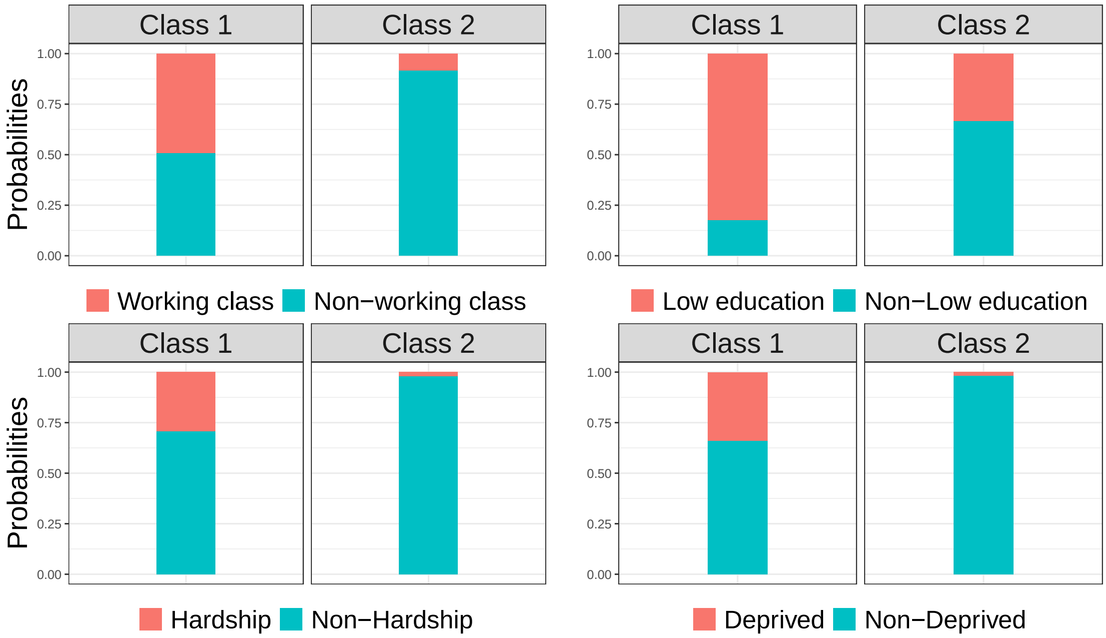
To assess the capacity of the estimated models to properly categorize households on this basis we can examine conditional response probabilities representing the probability of the response variable taking a particular value conditional on the household being in a given latent class, i.e., $p(Y_{ij} = y|U_i = \xi_u)$. These provide the risk of exposure to each variable depending on the allocated latent class, with a higher concentration of disadvantage clearly being expected in what is being taken as the multidimensional latent poverty class. Figures 2 to 3 report the conditional response probabilities for the parental and current generations respectively at the European level. These are presented as bar plots with the composition across each variable. For each variable, the bar on the left represents the poor latent class and the bar on the right the non-poor latent class.

Figure 2 shows clear stratification between the two classes for the parental generation. Class 1 has higher probabilities of households with working class parents, with low education, in economic hardship as well as in social and material deprivation. The opposite holds for Class 2. In Figure 3 we show evidence on the current generation latent classes. Class 1 is characterized by higher probabilities of income poverty, being working class, low educated, in financial hardship and in state of material or social deprivation. On the contrary Class 2 denotes lower probabilities of disadvantaged state in all the five dimensions. In Appendix B (Table B.1 and B.2) we complement with the conditional response probabilities by country.

Table 2 summarises these findings for the parental and current generations in terms of the probabilities shown in the Figures as well as the ratio between those for poor versus non-poor classes to bring out the scale of difference between them. We expect to see ratios above one for each of the dimensions included in the latent class models. For the parental generation the highest ratios are those for social and material deprivation and hardship, while social class and, mostly, education, display lower ratios but still above one. For the current generation the deprivation dimension is the one with the highest ratio, followed by the income poverty and the educational and hardship dimension, with the lowest ratio for the working class dimension. These results show that the two latent classes are clearly distinct in terms of prevalence of disadvantage in each generation, and in the expected direction.

Overall, as shown in Table 3, from the estimated latent class model for the parental generation the poor class corresponds to 25.7 % of the European sample, ranging from 5.4% in Sweden to 29.1% in Serbia. For the current generation the share of multidimensional latent poor households equals 20.4%, ranging from 7.8% in Germany to 42.7 in Greece.

Figure 2: Conditional response probabilities: parental generation



Notes: Conditional response probabilities are probabilities of the response variable taking a particular value, conditional on being in a given latent class. They are obtained from latent class estimation presented in Section 4. **Source**: Authors' elaborations based on EU-SILC 2019.

Figure 3: Conditional response probabilities: current generation

Notes: Conditional response probabilities are probabilities of the response variable taking a particular value, conditional on being in a given latent class. They are obtained from latent class estimation presented in Section 4. **Source**: Authors' elaborations based on EU-SILC 2019.

Table 2: Conditional response probabilities for multidimensional latent poverty dimensions in parental and current generation

Generation		Class 1		Class 2		Classes Ratio (1/2)
Parental	Low Education	82.60	(0.003)	33.55	(0.002)	2.46
	Non-low education	17.40	(0.003)	66.45	(0.002)	0.26
	Working class	49.32	(0.004)	8.40	(0.001)	5.87
	Non working class	50.68	(0.004)	91.60	(0.001)	0.55
	Hardship	29.23	(0.003)	1.99	(0.001)	14.67
	Non hardship	70.77	(0.003)	98.01	(0.001)	0.72
	Deprived	34.14	(0.004)	1.86	(0.001)	18.34
	Non deprived	65.86	(0.004)	98.14	(0.001)	0.67
Current	Income Poor	46.42	(0.003)	4.81	(0.001)	9.65
	Income non Poor	53.58	(0.003)	95.19	(0.001)	0.56
	Low Education	47.09	(0.003)	8.17	(0.001)	5.76
	Non-low education	52.91	(0.003)	91.83	(0.001)	0.58
	Working class	71.06	(0.003)	16.97	(0.001)	4.19
	Non working class	28.94	(0.003)	83.03	(0.001)	0.35
	Hardship	68.83	(0.004)	11.56	(0.001)	5.95
	Non hardship	31.17	(0.004)	88.44	(0.001)	0.35
	Deprived	28.05	(0.003)	0.22	(0.000)	129.37
	Non deprived	71.95	(0.003)	99.78	(0.000)	0.72

Notes: The latent class model used to estimate the conditional response probabilities for the parental and current generations are explained in Section 4. Standard errors in parentheses. **Source**: Authors' elaborations' based on EU-SILC 2019.

Table 3: Descriptive statistics on multidimensional latent poverty, by country

Country	Parental	Current	No. obs.
AT	13.96	9.96	4730
BE	16.53	12.12	5179
BG	20.50	29.47	6310
CH	6.52	8.39	4506
CY	19.53	21.06	3489
CZ	17.24	9.71	7149
DE	7.68	7.82	7660
DK	8.21	12.60	2019
EE	14.13	11.63	5613
EL	23.78	42.71	14207
ES	26.53	21.67	14732
FI	8.05	12.82	4219
FR	28.22	13.00	7242
HR	27.66	22.63	6791
HU	27.42	19.90	4450
IE	21.07	16.91	2014
IT	26.46	23.28	14639
LT	20.19	19.99	3585
LU	21.72	10.57	1983
LV	13.72	20.35	3518
MT	16.54	16.40	3870
NL	11.72	9.64	4535
NO	7.23	10.39	2447
PL	13.10	13.37	14930
PT	28.10	23.82	12275
RO	23.59	28.15	7004
RS	29.09	35.82	5832
SE	5.41	8.11	2030
SI	20.93	15.70	4301
SK	25.16	16.61	5961

Notes: The latent class model used to estimate the state of parental and current poverty are explained in Section 4. **Source**: Authors' elaborations based on EU-SILC 2019.

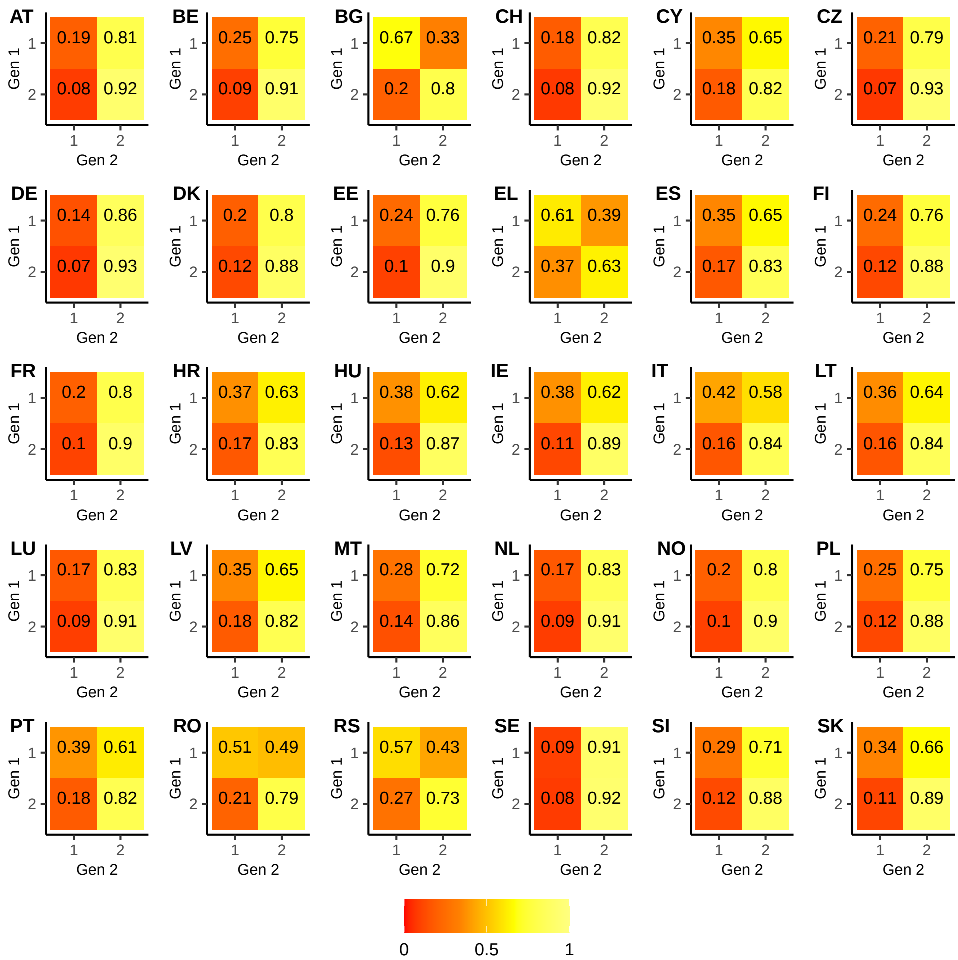
6 Intergenerational Mobility and Multidimensional Latent Poverty

We can now assess the intergenerational association between childhood poverty and current poverty based on the two latent classes for each generation identified in the previous section. To do so we first present in Figure 4 the transition matrix for each of the 30 European countries for which we have data. The parental state of latent poverty is depicted on the y-axis (denoted with Gen 1) while the current state of poverty is depicted on the x-axis (denoted with Gen 2), focusing on the probability of being in poverty conditional on growing up poor or non-poor (so each row of the transition matrix sums to one). The colours, from red to yellow, represent the density of each cell with red being lower shares, yellow higher ones, and orange in the middle. Persistence in poverty and non-poverty are shown in the top-left square and bottom-right square, respectively. The upper-right corner represents upward movements out of poverty, while the bottom-left corner are downward movements into poverty.

The figures in the top row of the transition matrices, showing the frequency of persistence in poverty and of exiting from it, show a very wide variation across countries. In terms of persistence we move from values of 0.06 in Sweden (6 out of 100 households with parents in state of latent poverty persist in the state in the following generation) to 0.72 in Bulgaria (72 out of 100 households with parents in state of latent poverty persist in the state in the following generation). In terms of the latter we move from values of 0.28 in Bulgaria (28 out of 100 households with parents in the state of latent poverty manage to exit that state in adulthood) to 0.94 in Sweden (94 out of 100 households with parents in the state of latent poverty exit that state in adulthood).

The figures in the bottom row of the transition matrices relating to those not in poverty in childhood are characterized by somewhat less but still substantial cross-country variability. Persistence in non-poverty spans from 0.58 (Greece) to 0.94 (Sweden), while downward mobility's range is from 0.06 in Luxembourg and Sweden to 0.42 in Greece. What stands out from the analysis, then, is the sizeable differences across European countries in the extent and composition of intergenerational latent poverty persistence.

Figure 4: Intergenerational transition matrices in multidimensional latent poverty state, EU countries

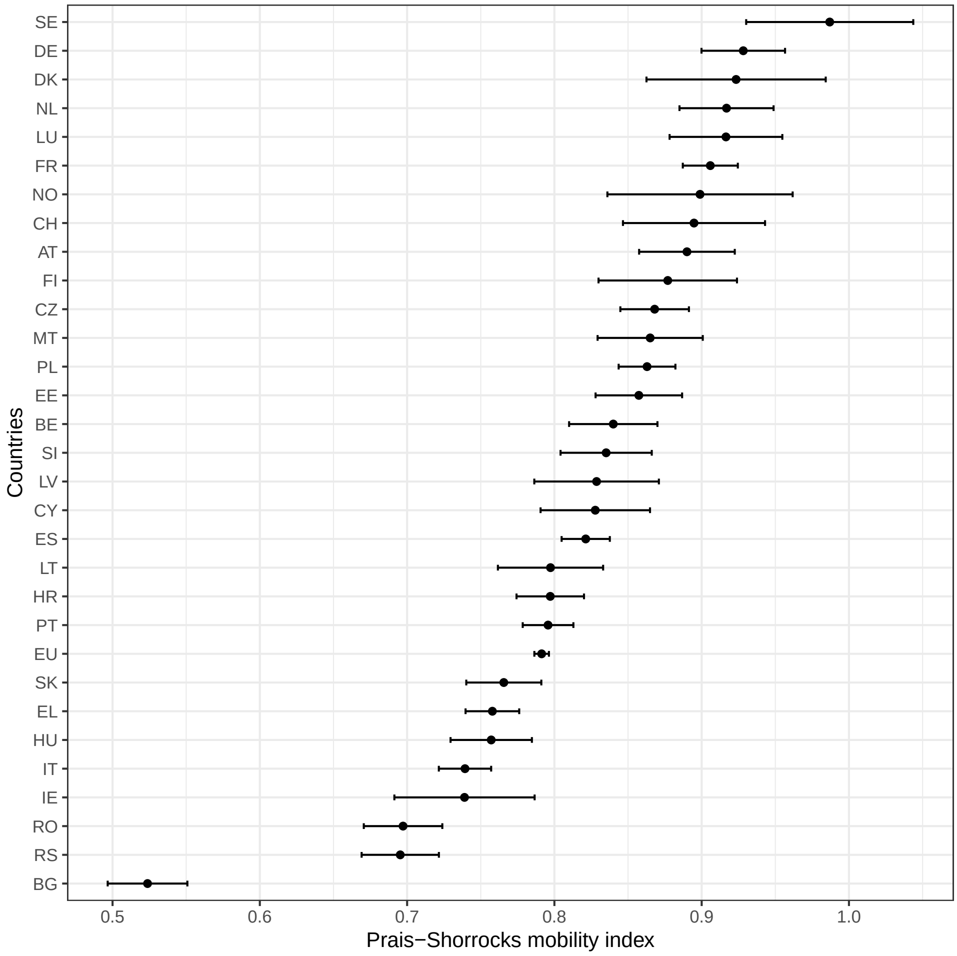


Notes: Each row of the country transition matrices sums up to 1 (values expressed in probability terms). The parental state is depicted on the y-axis, denoted by Gen 1. The current state is depicted on the x-axis, denoted by Gen 2. Class 1 corresponds to the depleted class in both generations. **Source**: Authors' elaborations based on EU-SILC 2019.

To capture these differences in mobility patterns more succinctly it is also helpful to use a summary mobility measure and here we employ the widely-used Prais-Shorrocks index (Shorrocks, 1978): $PS = \frac{k-tr(PS)}{k-1}$, where k is the number of classes in the matrix and $tr()$ is the matrix trace. The rationale for this index is that immobility is defined in relation to staying in one's own original class, taking into account only the diagonal terms in the matrix.

Figure 5 presents values for the Prais-Shorrocks index by country. There is once again significant variation across countries with values ranging from 0.6 to 1. Seen in terms of widely-used groupings of European countries on a geographical basis or into welfare state 'regimes', countries with relatively high mobility/low persistence include Sweden, Norway, Denmark, Finland from the Nordics and the 'continental' corporatist Northern European countries Austria, France, Germany, Luxembourg, and Switzerland. At the other end of the spectrum, with the lowest mobility/highest persistence, we see Bulgaria and Romania which have the lowest levels of average income and least developed welfare states in the EU along with non-EU member Serbia at a lower level of development. Somewhat surprising Ireland and Italy, with much higher levels of average income and more developed welfare states than those three outliers, display the next-lowest levels of mobility. In between these and the high-mobility countries lie other Mediterranean and post-socialist countries along with corporatist/continental Belgium. It is notable, however, that for a substantial proportion of country pairs the confidence intervals around their estimated mobility indices overlap, reflecting inter alia the limited size of some country samples.

Figure 5: Intergenerational mobility in multidimensional latent poverty, EU countries: Prais-Shorrocks mobility index



Notes: The confidence intervals are computed as $PS \pm z \cdot s/\sqrt{n}$, where PS stands for the Prais-Shorrocks index and s are the standard errors which are computed parametrically. **Source**: Authors' elaborations based on EU-SILC 2019.

7 Robustness and Reliability of the Results

As set out in Section 3, in estimating the latent class model up to this point we have incorporated the maximum amount of information available by including income for the current generation even though it is not available for the parental one, and have imposed a model with two classes. We now explore the robustness of our findings first when only the dimensions available for both generations are included, and then when the model is extended to allow for three or more latent classes. Finally, we consider concerns that may arise with respect to the reliability of the retrospective reports from survey respondents on circumstances in the household they were living in at age 14, on which our picture of those childhood circumstances rely.

7.1 Using a common set of variables across generations

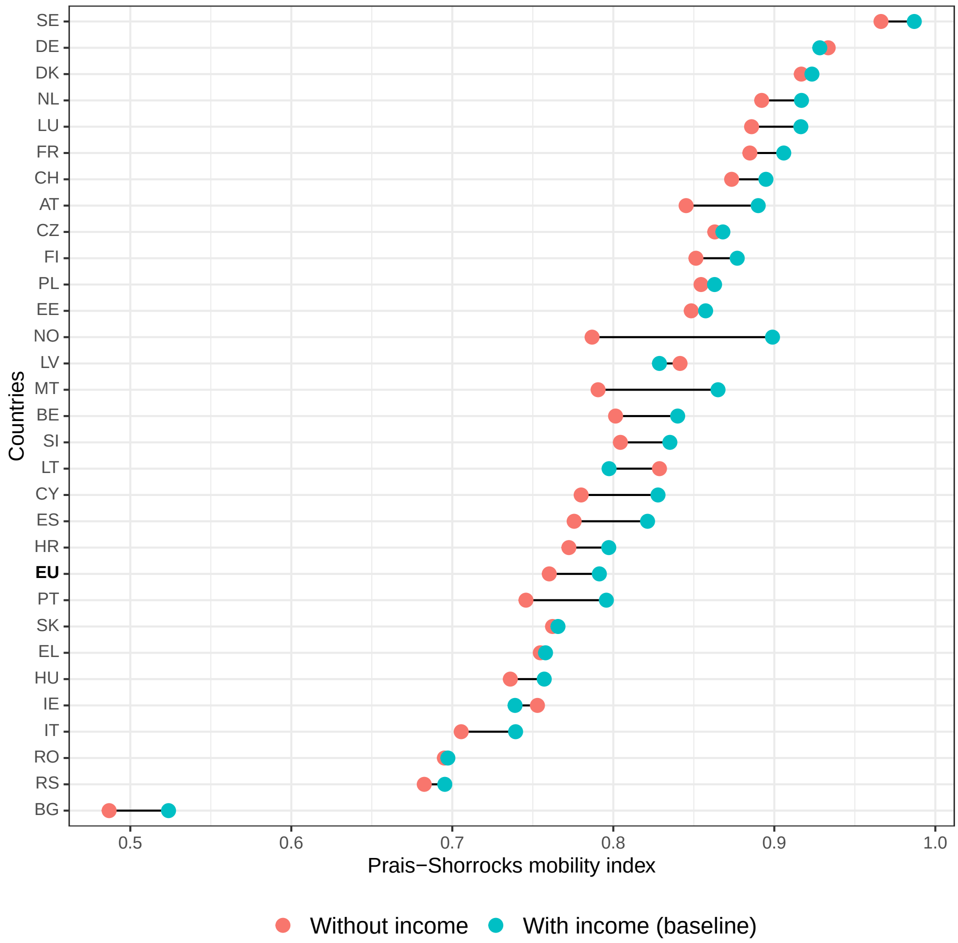
The latent class model presented in Section 4 is based on the use of all available information to derive the poverty state, so the model for the current generation is richer than that for the parental generation reflecting data availability. Data for the current generation includes household income, which often plays a central role in poverty measurement and might be seen as a particularly important gap in what is available for the parental generation. Here we assess whether our results for mobility are substantially different when income is omitted from the latent class model for the current generation.[5]

We estimate a model without income poverty for the current generation and obtain the latent poverty classification as before. In Appendix C (Table C.1) we illustrate the conditional response probabilities for the current generation model, as those for the parental generation remain unchanged. These values may be compared to the ones in Table 2 to verify that there is not any relevant change, apart from an increase in the class ratio of the deprived in the alternative model.

Figure 6 shows the comparison of Prais-Shorrocks mobility estimates between our baseline model (with income) and the one without income. Overall, we find a slight increase in this index across the entire sample when income is omitted. Table 4 shows how rankings change and the statistical significance of these differences in the Prais-Shorrocks indices. It shows 11 of the 30 countries with no change in ranking while only 8 countries report a statistically significant difference between the baseline and the adjusted estimates. However, a few countries show marked changes, with Norway shifting rank downwards by as much as 11 positions.

[5]As described earlier data for the current generation also includes a much more extensive set of deprivation items than obtained for the parental generation, which we retain here.

Figure 6: Intergenerational multidimensional latent poverty, EU countries: Prais-Shorrocks Index - alternative model for current generation without income dimension in the current generation



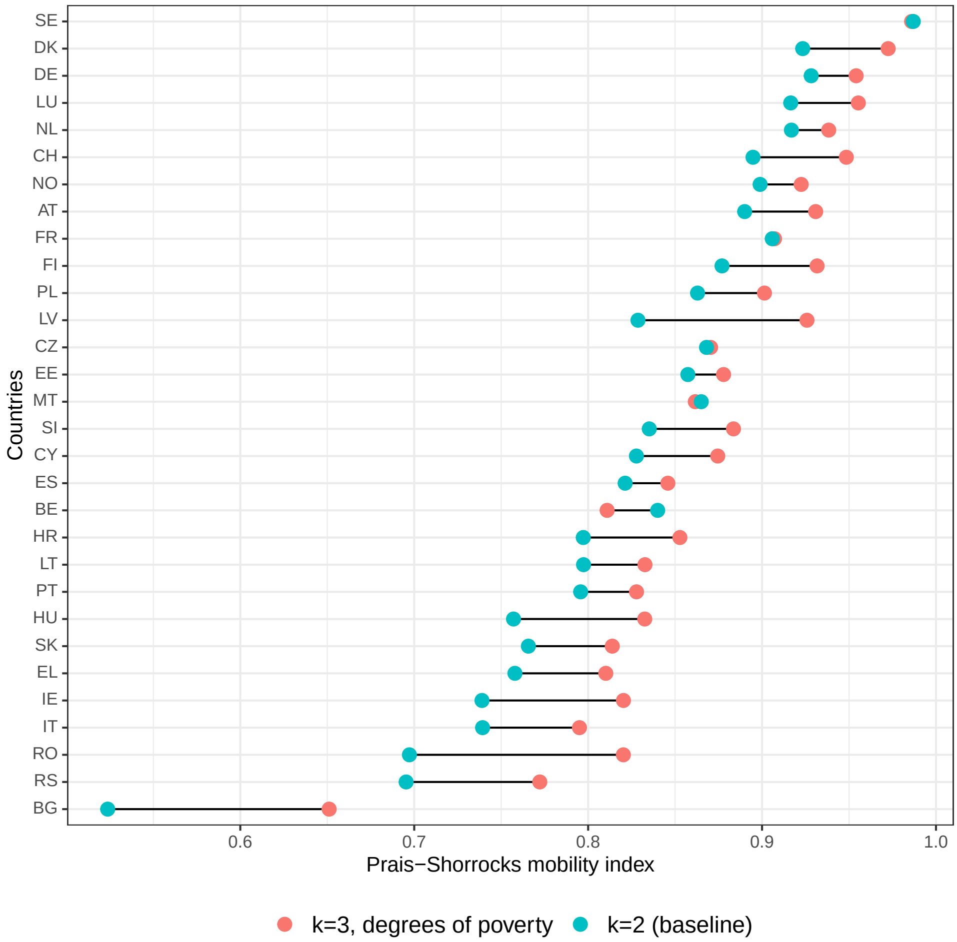
Notes: The latent class model used to estimate the state of parental and current poverty in this Figure are the ones in Section 4 without the income dimension for the current generation model. **Source**: Authors' elaborations based on EU-SILC 2019.

7.2 Modelling with More than Two Latent Classes

So far we have estimated the latent class model in terms of two-classes, on the a priori basis that the poverty concept we are dealing is essentially a binary one. There may still of course be varying degrees of poverty among the poor, but the core distinction on which we are focused is between the poor and non-poor. The fact that this distinction is difficult to make empirically does not take away from the importance of trying to do so. None the less, it is of significant methodological and empirical interest to ask what results the latent class model would produce from these data if the initial restriction to two classes is relaxed. We can first consider how the overall statistical fit of the model with two classes compares with models incorporating three, four or five classes. Appendix A shows the values for the BIC statistic commonly used for this purposes with different numbers of classes. This shows that a two-class model has a modestly higher BIC value than those for three-five classes, with then very little variation going from three to four to five.

We therefore present in Appendix D estimated conditional response probabilities from a latent class model with three classes, and in Figure 7 we display the Prais-Shorrocks mobility indices by country with this alternative model. Mobility measured this way generally increases with the number of latent classes, with particularly large increases for Latvia, Romania and Bulgaria. Overall the country rankings are rather stable, as shown in Table 4; a few countries see considerable changes in rank, notably Belgium, but it is only for Romania that the difference between the two models in the estimated values for the mobility index is statistically significant.

Figure 7: Intergenerational multidimensional latent poverty, EU countries: Prais-Shorrocks Index - alternative model for current generation with $k = 3$



Notes: The latent class model used to estimate the state of parental and current poverty in this Figure are the ones in Section 4 with three latent classes in both the generations. **Source**: Authors' elaborations based on EU-SILC 2019.

We also explored estimates from a latent model with four classes, obtaining results that are broadly similar to the three-class results presented. This provides some reassurance that our primary focus relying on a two-class model for a priori reasons has not done undue violence to the underlying data.

7.3 Including Control Variables in the Latent Class Model

As a final robustness robustness check we return to the estimation of our baseline two-class model and investigate whether the inclusion of age and cohort control variables affects the results presented in Section 5. The detailed estimation results presented in Appendix E show that this makes little difference to measured mobility out of/into poverty.

7.4 The Reliability of Retrospective Reports on Childhood Circumstances

Finally, all the information we have about parental circumstances are provided as retrospective assessments by current respondents of the situation of the the household in which they were living in at age 14. Particular concerns may arise with respect to the reliability of such data, given that respondents are being asked to think back what may be as much as 45 years ago, that their information about household circumstances then may be quite limited, and that what has happened to them in the interim may affect their perception of those circumstances. Unfortunately the reliability of such retrospective information has been little studied. Some assessments of retrospective information on parental education and occupation/social class have been carried out (see for example Hout and Hastings, 2016; Lavest et al., 2024), with results that may be regarded as relatively reassuring (though Lavest et al., 2024 find that offspring reports may tend underestimate the educational distance between themselves and their parents). However, it is the retrospective reports with respect to meeting basic needs and experiencing financial difficulties in the parental household that probably give rise to the greater concerns, and we are not aware of validation studies on those.

The core concern is not that such responses may sometimes be simply inaccurate but also that the frame of reference being used may vary across respondents in ways that introduce bias in the results of the exercise in which we are engaged. What respondents consider and report as a difficult financial situation in the parental household, for example, may of course vary with what they recall as commonplace in the country in question at that time. For our purposes that is not a problem as the underlying concept of poverty we are seeking to tap is itself relative, so it is not primarily differences across countries in such framing that may be of concern. Such retrospective responses could, however, be systematically related to how respondents have fared in the intervening years, with those who have experienced mobility reporting differently to those who have not; this would clearly introduce bias in estimates of mobility/persistence, though not necessarily in a way

Table 4: Model comparison by country, under a common set of variables and a three latent classes

Country	Baseline	No income		$k = 3$	
	(1)	(2)		(3)	
	ranking	ranking	p-value	ranking	p-value
AT	12	9	0.063	8	0.684
BE	16	15	0.083	26	0.761
BG	30	30	0.057	30	0.101
CH	7	8	0.538	5	0.638
CY	19	18	0.077	15	0.575
CZ	8	11	0.763	16	0.979
DE	2	2	0.786	4	0.828
DK	3	3	0.879	2	0.615
EE	11	14	0.669	14	0.821
EL	23	24	0.806	27	0.324
ES	20	19	0.000	19	0.756
FI	10	10	0.441	7	0.526
FR	6	6	0.120	11	0.989
HR	21	21	0.133	18	0.417
HU	26	25	0.292	21	0.308
IE	24	27	0.684	23	0.359
IT	27	26	0.009	28	0.463
LT	14	20	0.214	20	0.619
LU	5	5	0.288	3	0.678
LV	13	17	0.669	9	0.143
MT	17	12	0.006	17	0.968
NL	4	4	0.284	6	0.847
NO	18	7	0.022	10	0.815
PL	9	13	0.539	12	0.630
PT	25	22	0.000	22	0.717
RO	28	28	0.909	24	0.034
RS	29	29	0.498	29	0.116
SE	1	1	0.592	1	0.994
SI	15	16	0.167	13	0.541
SK	22	23	0.852	25	0.565

Notes: P-values refer to a statistical test for the null hypothesis of no difference between two Prais-Shorrocks indices, baseline and no income, in columns (2) and baseline and $k = 3$, in columns (3) . **Source**: Authors' elaborations based on EU-SILC 2019.

that affects how countries compare and are ranked in such terms. Investigation of such potential biases is clearly a priority though extremely challenging, with longitudinal data sources offering the greatest potential. For the present, and in all likelihood for some time to come, such retrospective data offers the only window into circumstances in the parental household for as broad-ranging a comparative exercise as presented here covering most European countries.

8 Conclusions

The transmission of poverty and disadvantage from one generation to the next is a particularly salient aspect of broader intergenerational mobility and inequality of opportunity, but very few studies seek to capture how the intergenerational persistence of poverty itself varies across countries. This is the gap which this paper has sought to address by exploiting data from the 2019 EU-SILC ad hoc module on intergenerational transmission of disadvantages and employing latent class analysis to fully incorporate all the information available in a flexible way that reflects the multidimensional nature of poverty with a minimum of structure imposed.

Estimating separate latent class models with two classes for both the parental and current generation, these two latent classes were clearly distinct in terms of prevalence of disadvantage, with the differences between them particularly pronounced for financial hardship in the parental generation and for material deprivation and ability to make ends meet in the current generation.

The intergenerational association between current poverty and poverty when growing up was assessed via transition matrices and summary mobility indices derived from them. Countries with relatively high mobility/low persistence include Nordic countries Sweden, Norway, Denmark and Finland and corporatist 'Continental' Austria, France, Germany, Luxembourg, and Switzerland. Those with the lowest measured mobility/highest persistence were Bulgaria, Romania and Serbia. Ireland and Italy, with much higher levels of average income, display the next-lowest levels of mobility. In between these and the high-mobility countries lie other Mediterranean and post-socialist countries along with corporatist/continental Belgium. For a substantial proportion of country pairs estimated mobility indices were not statistically different, reflecting inter alia the limited size of some country samples. The rankings obtained are similar though not identical to those produced by Bavaro et al., 2024) applying a different analytical approach to the same data. They also share some general features with the ranking of European countries in terms of social class found by Bukodi et al., 2020). (With income information for the parental generation available only for a limited number of countries, comparison with a ranking of most European countries in terms of overall intergenerational income mobility is not possible.)

The robustness of this ranking to specific analytical choices made in implementing the two-class model was investigated by re-estimating this model dropping income for the current generation (since it was not available for the parental generation), and by adding age/cohort controls. The results showed that country rankings in terms of measured mobility out of/into poverty were quite similar, albeit with some striking exceptions. Results from extending the model to more than two classes were also discussed, with country rankings seen to be similar in terms of mobility across three classes. The nature and limitations of the data available on household circumstances in childhood were also considered, despite these limitations these have the enormous advantage of allowing a very wide range of countries to be included. Leaving potential biases to one side, one may still question whether the information they provide is adequate to allow poverty, conceived in multidimensional terms, to be identified satisfactorily. While this has been the framing adopted here, not much may be lost if the results presented are instead taken as relating to the intergenerational transmission of multiple disadvantage.

The findings demonstrate how much more successful some European countries have been than others in reducing the transmission of poverty from one generation to the next. A priority for future research is the challenging task of teasing out which combination of institutions and policies underpin that success. Here our primary focus has rather been on demonstrating how latent class analysis can provide a flexible way to incorporate the complex structure of the data available for such a wide range of countries with a minimum of structure imposed.

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Appendices

Appendix A

Table 1: Latent class model goodness-of-fit statistics, BIC, parental and current generation

BIC	k=2	k=3	k=4	k=5
current generation	752149.3	746005.9	744815.6	744853
parental generation	642387.5	636161.4	636088.5	636149.2

Notes: The Bayesian information criterion (BIC) equals $-2logL + (logN)npar$, where L is the likelihood, $npar$ is the number of parameters in the model, and N is the number of participants. Lower BICs indicate better fit. **Source**: Authors' elaborations' based on EU-SILC 2019.

Appendix B

Table B.1: Conditional response probabilities of being in disadvantaged states by country, parental generation

Country	Class 1				Class 2			
	E	SC	H	D	E	SC	H	D
AT	85.29	57.03	57.52	39.38	14.08	2.79	5.39	1.34
BE	93.57	79.37	38.11	23.00	30.29	3.61	2.03	0.26
BG	94.38	83.08	18.79	47.16	19.00	7.64	0.55	2.03
CH	74.70	39.13	69.96	36.76	10.46	4.14	4.04	0.82
CY	96.90	61.99	41.64	42.86	39.28	3.09	1.38	0.25
CZ	96.13	63.64	25.45	43.40	38.22	1.75	1.04	1.75
DE	57.77	68.28	57.93	48.22	5.20	6.69	3.55	2.07
DK	82.18	62.07	50.00	41.95	18.48	3.14	2.33	0.60
EE	68.79	63.56	61.86	37.23	13.55	6.72	6.91	2.35
EL	97.41	40.52	26.73	67.49	56.65	3.23	0.72	1.66
ES	99.13	82.41	27.00	16.77	65.02	1.71	0.67	0.11
FI	85.33	76.95	36.23	23.05	19.00	5.61	2.50	0.46
FR	97.12	77.04	33.30	30.74	54.17	2.89	1.46	0.55
HR	93.76	79.75	41.23	28.21	28.83	9.24	2.38	0.83
HU	91.33	66.08	32.83	64.64	22.65	4.89	1.04	7.97
IE	93.27	86.32	36.10	21.52	26.59	11.54	1.91	0.19
IT	98.46	76.05	19.32	35.92	51.73	3.13	0.24	0.60
LT	88.56	80.81	26.20	39.36	17.28	9.34	1.41	3.10
LU	95.81	85.35	22.09	11.63	35.61	11.91	1.22	0.26
LV	79.01	73.72	40.69	43.61	13.47	8.32	3.91	3.20
MT	87.37	77.39	29.22	40.38	21.42	11.29	1.16	3.98
NL	94.43	85.54	21.25	17.42	41.15	2.80	0.40	0.28
NO	79.38	76.88	43.13	25.00	11.15	5.95	2.89	0.35
PL	81.23	58.33	45.47	49.79	20.45	8.35	2.73	2.40
PT	99.65	56.90	49.96	36.10	82.18	0.18	0.23	0.07
RO	82.05	50.77	28.13	81.80	11.02	13.34	0.67	13.19
RS	87.74	86.15	37.32	43.13	11.88	12.99	3.48	2.97
SE	87.74	68.87	47.17	18.87	18.97	2.55	3.17	0.26
SI	90.01	72.69	60.79	24.12	10.39	6.61	7.11	0.39
SK	96.92	72.15	22.61	48.56	36.19	2.25	0.95	2.34

Notes: We denote the various dimensions of latent multidimensional poverty with capital letters. E stands for education, SC stands for social class, H stands for hardship and D stands for deprivation.
Source: Authors' elaborations based on EU-SILC 2019.

Table B.2: Conditional response probabilities of being in disadvantaged states by country, current generation

Country	Class 1					Class 2				
	I	E	SC	H	D	I	E	SC	H	D
AT	64.49	30.03	86.42	66.32	19.84	4.39	4.62	13.04	3.01	0.00
BE	52.81	42.72	84.44	82.12	25.00	1.57	7.21	13.44	5.18	0.00
BG	44.91	45.21	72.73	90.42	51.71	2.10	3.19	14.96	21.84	0.00
CH	65.43	25.10	72.43	61.73	13.99	2.77	2.11	9.50	3.96	0.00
CY	31.33	32.87	69.51	92.73	36.78	0.43	6.06	14.20	17.56	0.00
CZ	50.96	21.73	83.07	77.96	21.57	1.73	2.13	20.24	5.06	0.00
DE	83.54	21.52	76.31	36.53	27.12	4.08	2.22	9.26	1.18	0.00
DK	56.12	26.62	89.93	70.50	23.74	1.06	4.73	16.12	2.39	0.00
EE	71.55	33.52	75.77	56.76	23.94	5.83	7.02	17.72	3.45	0.00
EL	38.41	39.60	67.63	97.62	33.98	1.09	4.72	11.48	50.06	0.00
ES	60.55	71.02	72.46	71.11	14.77	3.59	22.32	21.09	6.00	0.00
FI	66.56	16.88	88.13	47.81	20.00	1.97	2.15	17.21	1.92	0.00
FR	56.14	31.48	75.13	72.19	30.95	3.20	7.08	15.95	6.60	0.00
HR	54.32	33.81	80.32	87.80	25.89	2.03	5.71	21.28	16.10	0.00
HU	41.53	47.75	81.26	85.41	42.52	3.86	7.07	24.49	11.98	0.00
IE	57.75	44.79	79.72	68.45	29.30	2.41	8.44	13.50	5.97	0.00
IT	55.87	59.80	63.41	71.22	25.81	4.39	15.74	15.74	5.44	0.00
LT	57.16	18.01	78.72	67.80	40.57	3.51	2.57	20.59	6.60	0.00
LU	73.71	41.14	80.57	51.43	4.57	2.71	9.85	20.19	3.54	0.00
LV	65.64	22.99	76.51	75.03	38.69	5.02	4.54	20.19	8.27	0.00
MT	63.00	83.73	66.51	52.63	15.79	1.67	36.82	19.98	2.90	0.00
NL	61.35	26.76	84.59	60.27	17.30	2.18	6.22	12.36	2.28	0.00
NO	66.88	37.66	81.82	53.25	16.23	2.53	5.49	10.16	1.66	0.00
PL	65.25	21.86	79.94	70.19	21.09	7.18	3.11	21.31	5.53	0.00
PT	56.06	84.24	57.95	76.45	21.40	2.55	32.72	17.49	8.23	0.00
RO	58.82	41.61	55.65	71.77	46.13	4.16	6.67	18.99	11.99	0.00
RS	55.06	28.80	84.26	87.47	35.89	2.70	4.79	24.55	20.42	0.00
SE	78.72	23.40	79.79	39.36	6.38	2.43	1.76	9.35	1.39	0.00
SI	52.07	18.79	88.62	77.76	15.34	2.45	2.98	18.70	6.83	0.00
SK	47.43	29.81	81.05	85.24	45.81	2.48	1.77	17.55	15.58	0.00

Notes: We denote the various dimensions of latent multidimensional poverty with capital letters. I stands for income poverty, E stands for education, SC stands for social class, H stands for hardship and D stands for deprivation. **Source**: Authors' elaborations based on EU-SILC 2019.

Appendix C

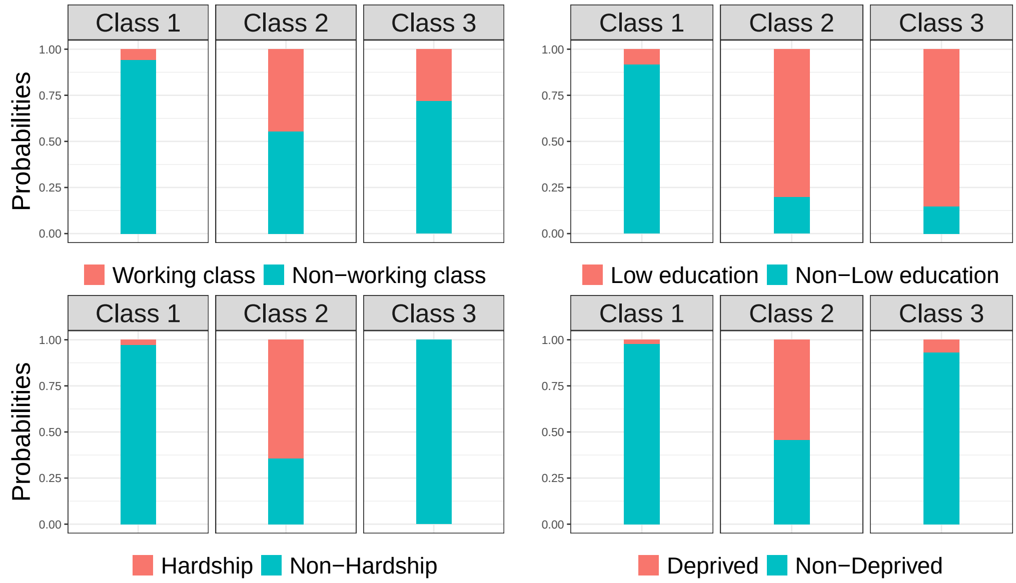
Table C.1: Conditional response probabilities for multidimensional latent poverty dimensions in parental and current generation, model without income dimension in the current generation

Generation		Class 1		Class 2		Classes Ratio (1/2)
Parental	Low Education	82.60	(0.003)	33.55	(0.002)	2.46
	Non-low education	17.40	(0.003)	66.45	(0.002)	0.26
	working class	49.31	(0.004)	8.40	(0.001)	5.87
	non working class	50.69	(0.004)	91.60	(0.001)	0.55
	hardship	29.23	(0.003)	1.99	(0.001)	14.67
	non hardship	70.77	(0.003)	98.01	(0.001)	0.72
	deprived	34.14	(0.004)	1.86	(0.001)	18.34
	non deprived	65.86	(0.004)	98.14	(0.001)	0.67
Current	Low Education	47.61	(0.004)	8.05	(0.001)	5.91
	Non-low education	52.39	(0.004)	91.95	(0.001)	0.57
	working class	69.88	(0.004)	17.29	(0.001)	4.04
	non working class	30.12	(0.004)	82.71	(0.001)	0.36
	hardship	70.34	(0.005)	11.19	(0.001)	6.28
	non hardship	29.66	(0.005)	88.81	(0.001)	0.33
	deprived	28.83	(0.003)	0.03	(0.000)	1124.06
	non deprived	71.17	(0.003)	99.97	(0.000)	0.71

Notes: The figures for parental generation are equal to those in Table 2 since in this version we are only modifying the current generation latent class model. Standard errors in parentheses. **Source**: own elaborations' based on EU-SILC 2019.

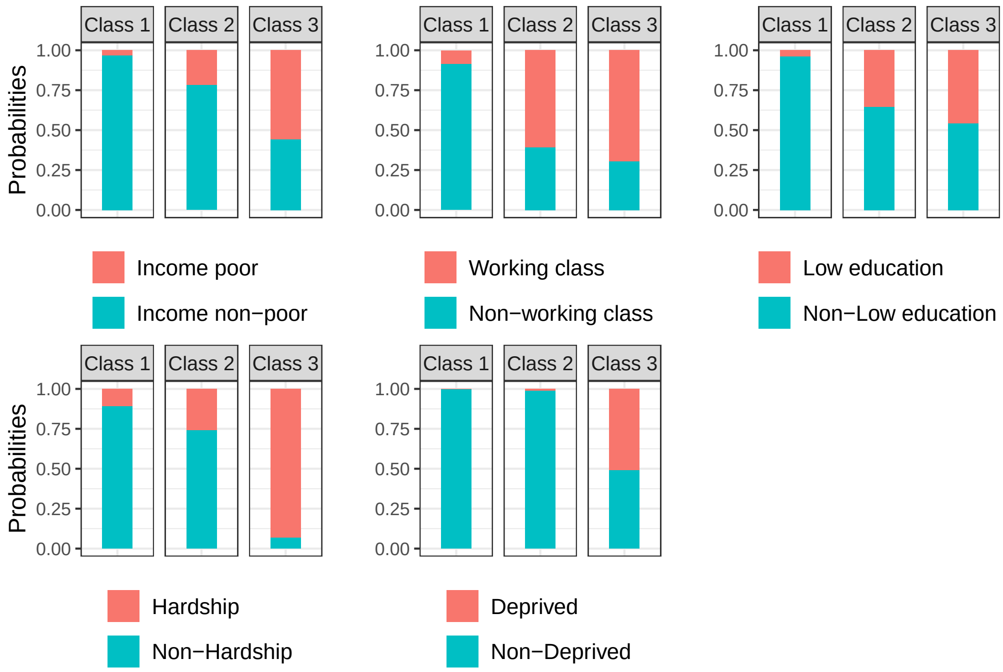
Appendix D

Figure D.1: Conditional response probabilities, model with three latent classes: parental generation



Notes: Conditional response probabilities are probabilities of the response variable taking a particular value, conditional on being in a given latent class. They are obtained from latent class estimation presented in Section 4. **Source**: Authors' elaborations based on EU-SILC 2019.

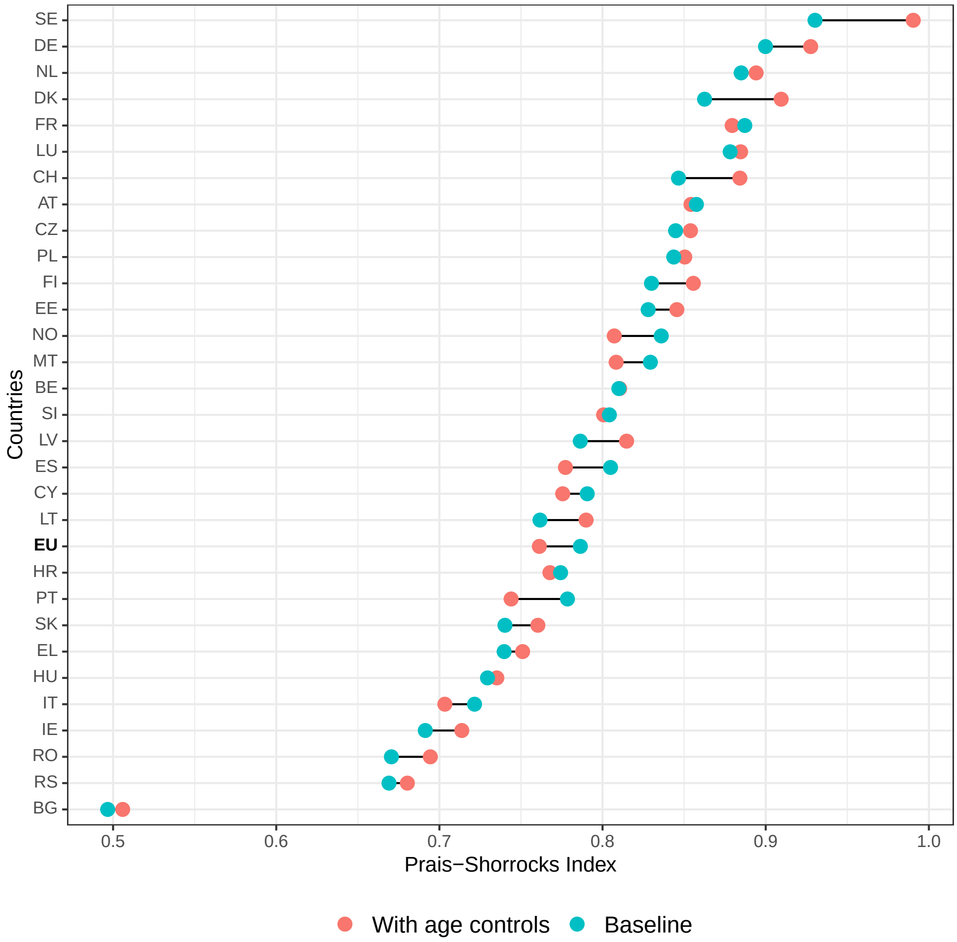
Figure D.2: Conditional response probabilities, model with three latent classes: current generation



Notes: Conditional response probabilities are probabilities of the response variable taking a particular value, conditional on being in a given latent class. They are obtained from latent class estimation presented in Section 4. **Source**: Authors' elaborations based on EU-SILC 2019.

Appendix E

Figure E.1: Intergenerational latent poverty, EU countries: Prais-Shorrocks Index - alternative models with age and cohort controls



Notes: The latent class model used to estimate the state of parental and current poverty in this Figure are the ones in Section 4 with the addition of age controls for the current generation model and cohort controls for the parental generation model. **Source**: Authors' elaborations based on EU-SILC 2019.